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INTELLIGENT AGENT-CONTROLLED ELEVATOR SYSTEM: ALGORITHM AND EFFICIENCY OPTIMIZATION

Gharbi A., Ayari M., El Touati Y. **Intelligent Agent-Controlled Elevator System: Algorithm and Efficiency Optimization.**

Abstract. The study introduces an innovative intelligent agent-controlled elevator system specially designed to improve passenger wait times and enhance the efficiency of high-rise buildings. By utilizing the classic single-agent planning model, we developed a unique strategy for handling calls from halls and cars, and combined with this strategy we significantly improved the overall performance of the elevator system. Our intelligent control methods are in-depth compared with conventional elevator systems, assessing three important performance indicators: response time, system capacity to handle multiple active elevator cars simultaneously, and average passenger waiting time. The results of the full simulation show that an intelligent agent-based model consistently exceeds conventional elevator systems in all measured criteria. Intelligent control systems have significantly reduced response times, and improved simultaneous elevator management and passenger wait times, especially during high traffic. These advances not only improved traffic flow efficiency, but also greatly contributed to passenger satisfaction and brought smoother and more reliable transport experiences within the building. Furthermore, the increased efficiency of our systems is in line with the goals of building energy management, as it minimizes unnecessary movements and idle time. The results demonstrate the system's ability to meet dynamic, high-occupation environment requirements and mark a significant step forward in intelligent infrastructure management.

Keywords: intelligent agent control, elevator system optimization, passenger waiting time.

1. Introduction. Elevator systems are integral to vertical transportation in modern buildings, but traditional control methods often result in suboptimal performance, particularly under fluctuating traffic patterns. Recent advancements in artificial intelligence offer new opportunities to enhance system efficiency. This paper introduces an intelligent agent-controlled elevator system designed to minimize passenger wait times through dynamic real-time optimization.

This paper addresses the complexities inherent in elevator system management within the context of intelligent agent control, focusing on optimizing operations to enhance performance. It introduces a classical single-agent project planning model specifically designed for elevator systems, incorporating advanced strategies for both hall call and car call processing. The primary objective is to improve elevator system performance by minimizing passenger waiting times and managing traffic flow more effectively. To achieve this, the paper outlines detailed procedures and algorithms tailored to these tasks.

Additionally, the proposed algorithms are validated through simulations, providing empirical evidence of their superior efficiency compared to conventional methods. The key contribution of this work is its comprehensive approach to elevator system optimization, which offers a pathway to developing smarter, more adaptive elevator solutions for modern buildings.

The state of the art in intelligent agent-controlled elevator systems reflects a convergence of technologies, including machine learning, real-time data analytics, IoT integration, and advanced algorithms. These advancements have paved the way for more efficient, adaptive, and user-centric elevator systems capable of optimizing transportation operations and minimizing passenger wait times.

Machine learning techniques, including reinforcement and deep learning, are applied to elevator systems for intelligent decision-making. These techniques enable agents to learn the best strategies through observation and interaction, improving efficiency and adaptability [1 – 4]. However, integration of machine learning into elevators brings challenges such as data collection burdens, model interpretation in safety-critical systems, adaptation to dynamic environments, avoidance of over-adaptation, addressing algorithmic biases, ensuring robustness and efficiently managing computational resources.

Real-time data analysis uses data such as elevator positions and passenger demand to optimize operations and reduce waiting times [5, 6]. However, in complex elevator environments, the need for reliable data flows, robust infrastructure, and effective data processing poses challenges, which can hinder computer resources and affect decision-making speed. To ensure data accuracy, reliability, and security, rigorous monitoring and validation processes are also required.

IoT integration in elevator systems includes sensors and devices to optimize operations using real-time data [7 – 9]. However, cybersecurity risks increase with IoT connections, which requires robust security measures such as encryption and regular audits. The management of a wide range of IoT devices requires scalable connections, efficient data processing, and solutions for interoperability challenges between different devices and platforms.

Advanced planning and optimization algorithms dynamically allocate elevator assignments, optimize traffic flow, and reduce waiting times taking into account passenger demand, elevator capacity and building traffic patterns in real time [10, 11]. However, this integration is subject to challenges due to the complexity of the computation, especially in large systems. The development and maintenance of sophisticated adaptive algorithms requires significant resources and expertise. System uncertainty and instability require robust validation, testing and reactive mechanisms for reliability and safety.

Advanced planning and optimization algorithms dynamically allocate the assignment of elevators, optimize traffic flow, and reduce wait times, considering passenger demand, elevator capacity and real-time traffic patterns [10, 11]. However, this integration is faced with challenges due to the complexity of the calculation, especially in large systems. Developing and maintaining sophisticated adaptive algorithms require considerable resources and expertise. Uncertainty and instability of the system require robust validation, testing and reactive mechanisms for reliability and safety.

Elevator systems are often complex and involve multiple elevators serving different floors simultaneously. Multi-agent systems employ intelligent agents to coordinate and synchronize the actions of multiple elevators, resulting in improved traffic flow, reduced congestion, and enhanced transportation efficiency.

The state of the art in intelligent agent-controlled elevator systems reflects a convergence of technologies, including machine learning, real-time data analytics, IoT integration, and advanced algorithms. These advancements have paved the way for more efficient, adaptive, and user-centric elevator systems capable of optimizing transportation operations and minimizing passenger wait times.

This paper makes significant contributions by proposing new controls and strategies for optimizing the handling of hall calls, moving car procedures and handling of car calls in elevator systems. The paper further validates these contributions by simulation-based assessments, highlighting improvements in key performance metrics such as reduced passenger wait times, optimized traffic flow, increased energy efficiency and increased system response.

The remainder of this paper is organized as follows: Section 2 elaborates on the elevator problem and the challenges associated with traditional control approaches. Section 3 discusses the proposed control actions and strategies for optimizing elevator system efficiency. Section 4 presents the single-agent classical planning task model and its components, including hall call handling, move car procedures, and car call handling. Section 5 details the simulation setup and results, showcasing the efficacy of the proposed algorithms. Finally, Section 6 concludes the paper with a summary of contributions, insights into future research directions, and implications for the field of elevator system management.

2. An Elevator Problem. The miconic planning domain [15 – 19] involves transporting several passengers between different floors of a building using an elevator that can move up or down between floors, and passengers can enter or leave the elevator on each floor. Each passenger has an origin and a destination floor, and the initial floor f0 of the elevator is given. There are two types of actions in this domain: for each floor f, the "up(f)" and "down(f)" actions are considered, signifying the change in the current floor resulting from the action taken. This conceptualization yields a total of 2np + 2(nf – 1) distinct actions, where np represents the count of passengers and nf signifies the number of floors in the system. It is imperative to note that the system architecture excludes the provision of an "up" action from the topmost floor or a "down" action from the bottommost floor, reflecting the physical constraints inherent in such transport systems.

Figure 1 shows the resulting automaton where:

– The diagram has two states, "i" and "j", which represent the current floor of the elevator.

– Both states are initially in an "Idle" state, indicating that the elevator is not moving.

– The transitions between states are represented by "MoveDown" and "MoveUp" actions. These actions are triggered by conditions R_i, which represent requests for the elevator to move to a different floor.

Figure 1 illustrates how the elevator system responds to these requests by changing its state (i.e., moving to a different floor).

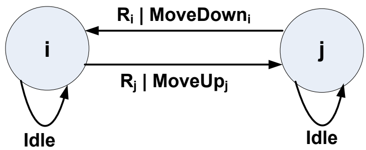

Fig. 1. Elevator automaton

The input set, represented as I = {R_i}, delineates the requested floors within the system, where R_i signifies a request for the i^{th} floor. Correspondingly, the output set O = {d_j, n, u_j} encapsulates directives regarding the elevator's movement, including the intended direction and destination floor. For instance, d_i denotes a downward movement to the i^{th} floor, u_j denotes an upward movement to the j^{th} floor, and n indicates the elevator should remain in an idle state.

The set of states, denoted as S = {S_i}, characterizes the elevator's current floor position within the system. Illustrated in Figure 1, when the elevator is situated at state S_i and receives a request for the j^{th} floor (R_j), it will actuate a downward movement (d_j) to floor j, thereby transitioning from state S_i to state S_j. This delineation establishes a clear framework for modeling the elevator's dynamic behavior based on input requests and current state conditions.

3. Control Actions. Elevator operations are constrained by a predefined set of permissible actions dictated by the system's operational rules. When an elevator is positioned on the floor, it faces the decision to either ascend or descend. While in transit between floors, it must choose between halting at the upcoming floor or bypassing it. These actions, however, are subject to constraints influenced by passenger expectations and operational guidelines. Notably, the elevator is obliged to accommodate passenger requests for disembarkation or change of direction before proceeding past a floor. Moreover, certain principles are integrated into the system to reflect foundational knowledge. These principles dictate that the elevator must halt only if there are passengers intending to enter or exit, avoid picking up passengers if another elevator is already stationed on that floor, and prioritize upward movement over downward movement. Consequently, the available choices for each elevator are limited to halting or continuing its trajectory. As the time taken to execute these actions varies among elevators, they perform their actions asynchronously, leading to staggered completion times.

To evaluate the cost associated with a plan π, the following formula can be employed:

$$C(\pi) = \sum_{ai \in \pi} c(a_i),$$

where $\sum_{ai \in \pi}$ means to sum up the cost of each action in the plan π, and c(ai) is the cost of each individual action.

The flowchart delineated in Figure 2 elucidates the operational sequence of the proposed model, which initiates the generation of a hall call within the elevator system. Initially, the model assesses the availability of elevators, discerning if multiple elevators are unoccupied. In such instances, the model employs a selective approach to designate the elevator with the shortest waiting time to respond to the hall call and dispatch it to the requested floor. Conversely, when only a single elevator is available, it is directed to the requested floor using the same selective approach. However, in scenarios where no elevators are vacant, the model undertakes a more intricate decision-making process. This involves calculating the movement direction and assessing the capacity of each elevator. By aligning these parameters with the requirements of the hall call, the model employs a collective approach to determine the most suitable elevator for the task and assigns it to respond to the request.

The model utilizes two distinct categories of variables: state variables and action command variables. State variables encapsulate the current operational status and conditions of the elevators within the system, aiding in decision-making processes. Conversely, action command variables are triggered upon the generation of hall calls or car calls, initiating decision pathways and directing elevator movements accordingly. This structured approach optimizes elevator response times, resource utilization, and overall system efficiency, enhancing passenger experience and operational performance within the elevator system.

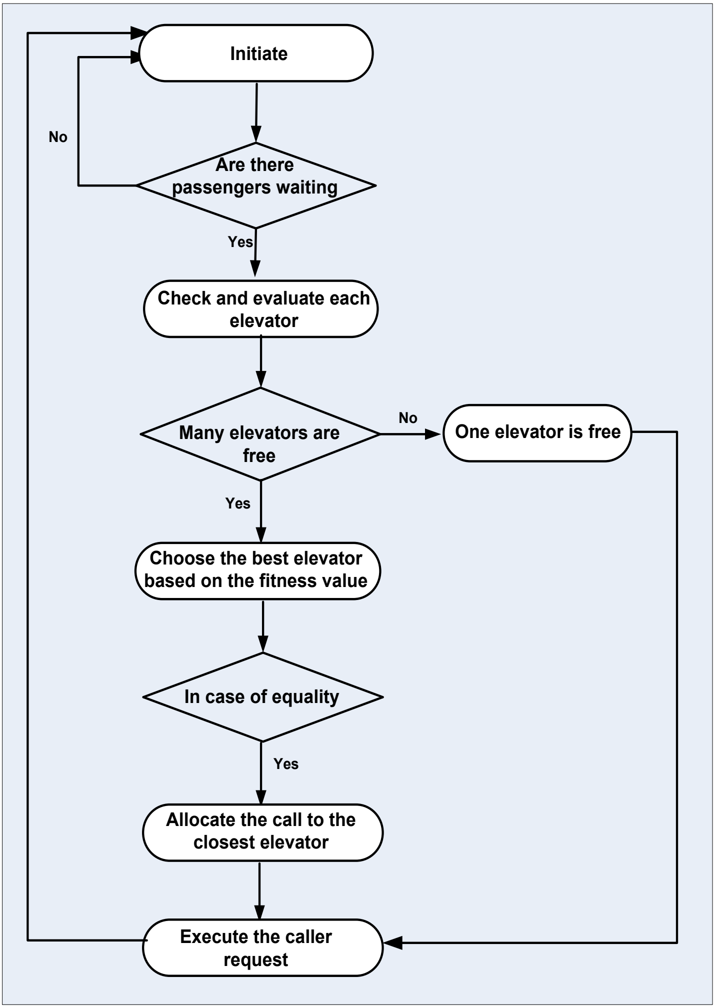

Fig. 2. Flowchart of conventional elevator control system

4. Single-agent classical planning task for an elevator system. The elevator system operates within a building encompassing multiple floors, denoted by numbers ranging from 1 to n (where n represents the total floors in the building). The elevator's movement capability is limited to traversing one floor at a time, either ascending or descending, with the flexibility to halt at any floor along its route. Additionally, the elevator has a predefined passenger capacity of c, and each passenger is associated with a specific destination floor within the building. Passengers can only embark and disembark at floors where the elevator makes stops, adhering to operational protocols.

4.1. Intelligent Agent-Controlled Elevator System. The intelligent control agent for managing multiple elevators and calls operates by implementing a closed-loop system that continuously uses feedback to reassess key input parameters for the decision-making process. The agent's primary goal is to minimize passenger waiting times by dynamically assigning elevators to calls based on real-time conditions. Various contextual parameters, including the current floor, movement direction, current status, and waiting time, are considered. The waiting time (T waiting) for arrival at the departure floor is dynamically calculated in real time, considering the current direction of movement and the stop-request queue.

The input data for the proposed system consists of fundamental operational information, including:

1) The current movement direction of each elevator (upward, downward, or stationary).

2) The precise position of each elevator and the corresponding landing floors.

3) The log of active car calls within each cabin.

During each iteration, the control agent evaluates potential assignments, selecting the one with the optimal fitness (i.e., the best match between elevator and call that minimizes waiting time). Once the best assignment is determined, it is finalized, and the system recalculates the remaining options, factoring in the newly fixed allocation and any changes in the system's state, such as updated elevator positions or new calls.

When the control loop is first executed in a building with (k) elevators and (n) landing calls, the agent must evaluate a maximum number of decision-making processes. With each subsequent iteration, one less landing call needs to be evaluated, as the best allocation from the previous iteration is fixed and removed from the pool. This process continues until all landing calls have been assigned to elevators.

By performing this iterative process, the intelligent control agent effectively reduces the complexity of the problem, despite the large number of possible solutions. The algorithm is designed to find an optimal or near-optimal solution to this NP-hard problem without imposing significant computational demands. The agent not only optimizes individual elevator-call assignments but also dynamically adjusts the order in which calls are dispatched, ensuring efficient and responsive elevator operation in real time.

In practical implementation, the comprehensive up-peak energy-saving scheduling strategy is outlined as follows, with the corresponding flowchart depicted in Figure 3. During each scheduling cycle, the intelligent controller agent, using the proposed algorithm, independently retrieves the current state of each elevator, all active call signals, and the average waiting time from the previous scheduling cycle. The intelligent controller agent then determines the number of elevators required to serve the waiting passengers, guided by an energy-time piecewise function.

Subsequently, the intelligent controller agent selects the specific elevators to deploy, based on an optimization scheduling solution aimed at minimizing waiting time for passengers. After iterative optimization, an optimal scheduling plan is derived, and all elevators are dispatched accordingly.

Once the elevators are scheduled based on the optimal plan, the scheduling algorithm evaluates whether each elevator has been dispatched in the current cycle. Each elevator's operation is governed by specific logic based on its active or inactive state, as illustrated by the four operational logics in Figure 3:

a) If an elevator is dispatched and currently ascending with passengers, it will complete the ongoing transport task and then return to the lobby floor to pick up new waiting passengers.

b) If an elevator is dispatched but currently stationary, it will switch from inactive to active and proceed directly to the lobby to serve passengers.

c) If an elevator is not dispatched but currently transporting passengers, it will complete its current task, remain stationary, and await a new task in the next scheduling cycle.

d) If an elevator was not dispatched in both the previous and current scheduling cycles, it will remain inactive.

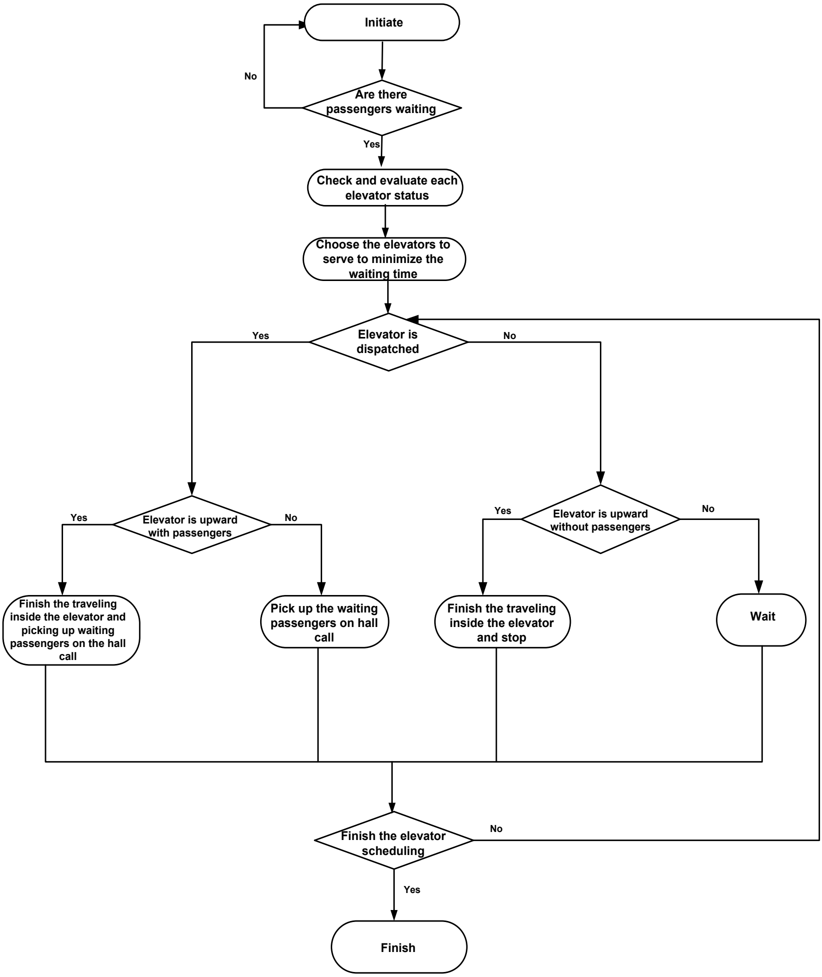

Fig. 3. Flowchart of intelligent elevator control system

Running example.

Suppose we have an intelligent control system with three elevators and eleven floors. Elevator 1 is on floor 4, Elevator 2 is on floor 3, and Elevator 3 is on floor 7. Elevator 1 wants to move up to floor 8, Elevator 2 wants to move down to floor 2, and Elevator 3 to move up to floor 10 (Figure 4).

To minimize waiting times, the intelligent control system allocates Hall Call 6 to Elevator 1, Hall Call 2 to Elevator 2, and Hall Call 9 to Elevator 3.

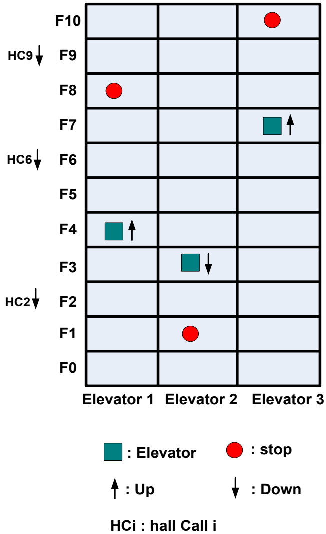

Fig. 4. A simplified example of an intelligent elevator control system composed of 11 floors and 3 elevators

4.2. Intelligent Agent Control in Action. To illustrate how the intelligent agent controls elevator efficiency based on the outlined algorithm, let's consider a scenario in a busy office building. The building has several elevators serving multiple floors, and the intelligent agent is tasked with optimizing elevator operations to minimize wait times and improve overall efficiency.

– Hall Call Handling: When a passenger on a floor requests an elevator by pressing the up or down button, the HALL_CALL procedure is activated. The agent checks the status of each elevator, identifying the one closest to the requested floor and moving in the same direction. If all elevators are idle, the first available one is assigned. The selected elevator is then directed to the requested floor, minimizing travel time and improving efficiency.

– Car Call Handling: When a passenger inside an elevator presses a button to select a destination floor, the CAR_CALL procedure is invoked. The destination floor is added to the elevator's destination queue. If the elevator is idle, it is activated, and its direction is set based on the selected floor relative to its current position. The elevator then moves towards the destination floor, optimizing its path to efficiently serve passengers.

– Move Car Procedure: The MOVE_CAR procedure controls the elevator's movement based on its current state and direction. If the elevator is moving up, it visits the lowest floor in the up queue or destination queue. If there are no requests in either queue, all requests in the destination queue are cleared, and the elevator's state is set to idle. Similarly, when moving down, the elevator visits the highest floor in the down queue or destination queue, adjusting its direction and state accordingly.

By employing these procedures, the intelligent agent optimizes elevator operations, reducing wait times for passengers, and enhancing overall efficiency in the building's transportation system.

4.2.1. Hall Call Handling. The first procedure, HALL_CALL, handles hall calls from a floor with a given direction. If the direction is up, the floor is inserted into the Up_wQ queue; otherwise, it is inserted into the Down_wQ queue. If the elevator is idle, its state is set to active, and the elevator is moved in the direction of the hall call. The MOVE_CAR procedure is called to move the elevator.

We added a loop to check the distance of each elevator to the requested floor and selected the one with the closest position and in the same direction. If all elevators are idle, we will use the first one found in the loop. Then we assigned the request to the selected elevator and added it to its destination queue. If the selected elevator is idle, we set its moving direction to the direction of the destination queue and start moving the car using the MOVE_CAR procedure (Listing 1) to assign the new request to the elevator with the closest current position and in the same direction.

```
min_distance ← infinity
selected_elevator ← null
for each elevator e in the system
        if (e.state = IDLE)
            selected_elevator ← e
            break
        else if ((d = UP) and (e.current_position ≤ f) and (e.moving_direction = UP)
    and ((f - e.current_position) < min_distance))
            selected_elevator ← e
            min_distance ← f - e.current_position
        else if ((d = DOWN) and (e.current_position ≥ f) and (e.moving_direction =
    DOWN) and ((e.current_position - f) < min_distance))
             selected_elevator ← e
             min_distance ← e.current_position - f
      end if
end for
if (selected_elevator = null)
        if (d = UP)
             insert(f, Up_wQ)
        else
            insert(f, Down_wQ)
```

```
            end if
    else
        selected_elevator.dest_q.add(f)
        if (selected_elevator.state = IDLE)
                selected_elevator.state ← ACTIVE
                selected_elevator.moving_direction ← d
        end if
        selected_elevator.MOVE_CAR()
    end if
    END
```

Listing 1. Procedure HALL CALL(source floor f, Direction d)

4.2.2. Move Car Procedure. The second procedure, MOVE_CAR, moves the elevator based on the direction it is traveling. If the elevator is moving up, it visits the lowest floor in the Up_wQ or the dest_q (destination queue) in the up direction. If there are no requests in either queue, all requests in the dest_q are removed. If all queues are empty, the elevator state is set to idle. If the elevator is moving down, it visits the highest floor in the Down_wQ or the dest_q in the down direction. If there are no requests in either queue, all requests in the dest_q are removed. If all queues are empty, the elevator state is set to idle. The procedure then sets the moving direction to the opposite direction and calls the VISIT procedure (Listing 2).

```
While (ElevState = ACTIVE) do
    If (MovingDirection = UP) then
            VISIT (Lowest floor in Up_wQ or dest_q in this direction)
            If no request in Up_wQ or dest_q in this direction then
                    Remove all requests in dest_q
                    If all queues are empty then
                            ElevState ← IDLE
                    else
                            MovingDirection← DOWN
                            VISIT (Highest floor in Down_wQ or dest_q)
                    End if
            End if
    Else // moving direction is down
            VISIT (Highest floor in Down_wQ or dest_q in this direction)
            If no request in Down_wQ or dest_q in this direction then
                    Remove all requests in dest_q
                    If all queues are empty then
                            ElevState ← IDLE
                    Else
                            MovingDirection← UP
```

```
                    VISIT (Lowest floor in Up_wQ or dest_q in destination)
                End if
            End if
        End if
    End while
    End
```

Listing 2. Procedure MOVE_CAR()

4.2.3. Car Call Handling. The third procedure, CAR_CALL, handles car calls to a destination floor. The floor is inserted into the dest_q queue. If the elevator is idle, its state is set to active, and the elevator is moved in the direction of the car call. The MOVE_CAR procedure is called to move the elevator (Listing 3).

```
Insert (f, dest_q)
If (ElevState = IDLE) then
    ElevState ← ACTIVE
    //If f is higher than current car position then
    If (f > currentElvPos) then
            MovingDirection ← UP
    else
            MovingDirection ← DOWN
    End if
    MOVE_CAR()
End if
  End
```

Listing 3. CAR_CALL(destination floor f)

5. Simulation. In this study, we conduct a comparative analysis between two distinct scenarios: our prior research involving a conventional elevator system [20] and a novel intelligent control elevator system designed to optimize passenger service based on proximity. The conventional elevator system represents a baseline model characterized by traditional operational algorithms and rules governing elevator movements and passenger interactions. In contrast, the intelligent control elevator system integrates advanced algorithms and decision-making processes to dynamically adjust elevator operations based on passenger location and demand, prioritizing minimizing average waiting time. The comparison between these two systems aims to assess the efficacy, performance improvements, and potential benefits of adopting intelligent control strategies in elevator systems, particularly in scenarios where passenger proximity influences service allocation and response times.

Figure 5 presents the response times of an intelligent control system compared to a conventional system over a 3600-second period. From 0 to 600 seconds, the intelligent system's response time increases from 0.01 to 0.12 seconds, while the conventional system rises from 0.015 to 0.20 seconds, with the intelligent system maintaining a consistent advantage. Between 600 and 1500 seconds, the intelligent system peaks at 0.20 seconds, whereas the conventional system reaches 0.40 seconds, highlighting a significant performance gap. In the later stages (1600 to 3600 seconds), the intelligent control system stabilizes, fluctuating between 0.05 and 0.29 seconds, while the conventional system plateaus between 0.10 and 0.49 seconds, indicating less adaptability. Overall, the intelligent control system consistently shows lower response times across all intervals, with a maximum of 0.29 seconds compared to 0.49 seconds for the conventional system, suggesting greater efficiency in managing increasing passenger demand.

Overall, the intelligent control system is significantly more effective than the conventional system in handling varying passenger arrival rates. Its ability to maintain lower response times, even as demand increases, highlights its potential for enhancing operational efficiency in vertical transportation systems.

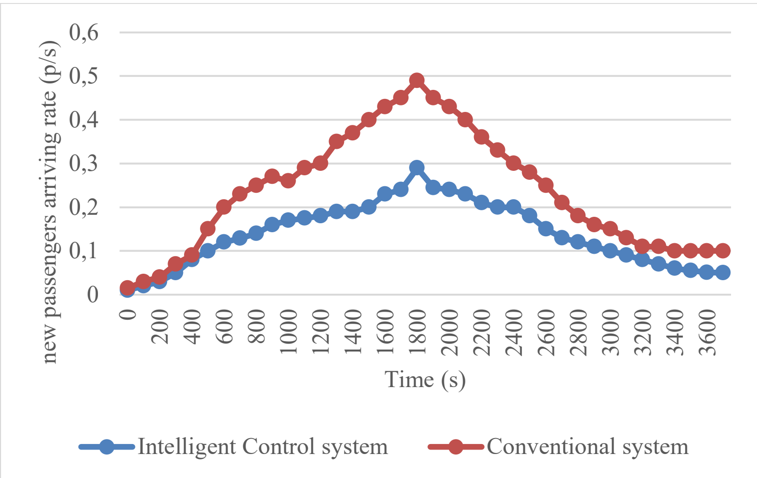

Fig. 5. Curves of up-peak new passengers arriving rate

Figure 6 presents a comparison of the performance of an Intelligent Control System and a Conventional System over time, focusing on their ability to manage active cars simultaneously. The data indicates that the

Intelligent Control System consistently manages fewer active cars compared to the Conventional System, suggesting that it is more proficient in optimizing the utilization of operational cars. Additionally, the Intelligent Control System appears to sustain its performance over a longer duration, indicating greater resilience to fluctuations in demand and the ability to maintain a high level of service for extended periods, contrasting with the performance of the Conventional System.

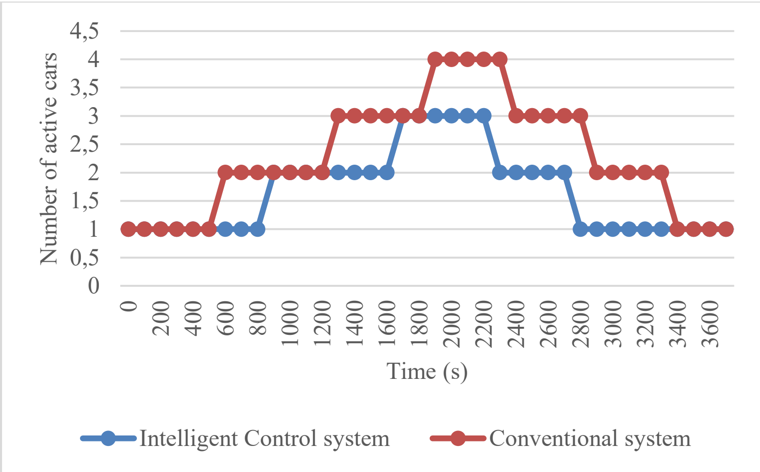

Fig. 6. Number of Elevators Dispatched During Up-Peak Periods

The simulation is set to run for a fixed period of one hour, allowing for the collection of sufficient data. During this time, the passenger arrival rate varies across different floors to simulate both peak and off-peak periods. For each control method, calls are assigned to elevators, and the elevators' responses are simulated. The key metric for evaluating performance is the average waiting time, which measures the time passengers wait for an elevator under both control scenarios.

Figure 7 presents the average waiting time in 21 simulations revealing that the intelligent control system significantly exceeds the conventional system, with an average waiting time of approximately 17.14 seconds compared to 29.14 seconds for the conventional system. The intelligent system shows constant low variability, with waiting times of 14 to 20 seconds, while the conventional system shows higher fluctuations, reaching a maximum of 33 seconds. Significant differences are noted in simulations 1, 3 and 11, where the efficiency of the intelligent system is particularly pronounced. Overall, the implementation of intelligent control mechanisms can improve the efficiency of operations and improve passenger experiences in vertical transportation systems, making them a more suitable choice for managing dynamic passenger requirements.

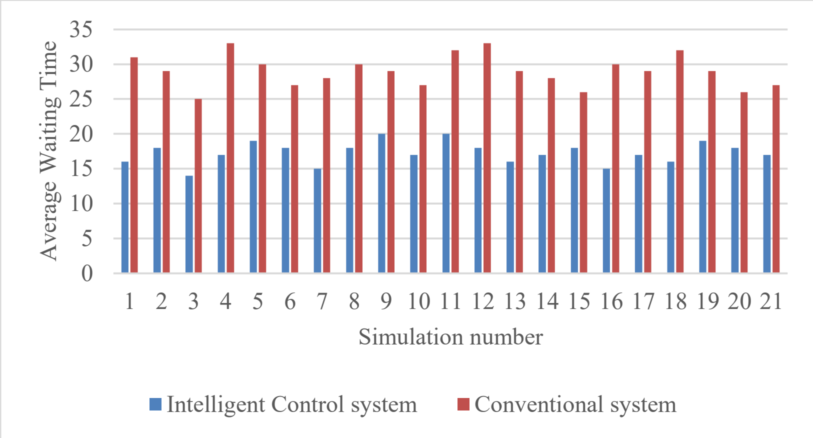

Fig. 7. Comparison of Average Waiting Times: Intelligent Control System vs. Conventional System

6. Conclusion. In conclusion, the proposed intelligent agent-controlled elevator system effectively reduces passenger wait times and optimizes traffic flow in real time. The study contributes a novel approach to elevator control, demonstrating significant improvements over traditional systems. Simulation-based evaluations validate the effectiveness of the proposed algorithms and demonstrate significant improvements in system performance metrics. However, the proposed intelligent control system faces limitations in integrating with existing elevator infrastructures, particularly in older buildings, where retrofitting could be costly and complex. Scalability is also a concern, as the system's effectiveness may decrease in larger buildings, leading to potential delays and data management challenges. Additionally, the system's reliance on accurate, real-time data could be problematic in environments with outdated sensors and communication networks.

Future research may focus on the assessment of implementations and scalability of intelligent agent-controlled elevator systems in the real world, the development of machine learning for elevator operations, the integration of IoT for real-time data optimization, and the collaboration with industrial partners for practical implementation, the improvement of urban mobility and construction management.

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ИНТЕЛЛЕКТУАЛЬНАЯ СИСТЕМА ЛИФТОВ, УПРАВЛЯЕМАЯ АГЕНТАМИ: АЛГОРИТМ И ОПТИМИЗАЦИЯ ЭФФЕКТИВНОСТИ

Гарби А., Айяри М., Эль Туати Я. **Интеллектуальная система лифтов, управляемая агентами: алгоритм и оптимизация эффективности.**

Аннотация. В исследовании представлена инновационная интеллектуальная система лифтов, управляемая агентами, специально разработанная для сокращения времени ожидания пассажиров и повышения эффективности высотных зданий. Используя классическую модель планирования с одним агентом, мы разработали уникальную стратегию обработки вызовов из коридоров и автомобилей, и в сочетании с этой стратегией мы значительно улучшили общую производительность лифтовой системы. Наши интеллектуальные методы управления подробно сравниваются с традиционными системами лифтов, при этом оцениваются три важных показателя эффективности: время отклика, способность системы одновременно обрабатывать несколько активных кабин лифта и среднее время ожидания пассажира. Результаты полного моделирования показывают, что интеллектуальная модель на основе агентов неизменно превосходит обычные системы лифтов по всем измеряемым критериям. Интеллектуальные системы управления значительно сократили время отклика и улучшили одновременное управление лифтами и время ожидания пассажиров, особенно во время большой загруженности. Эти усовершенствования не только повысили эффективность потока трафика, но и в значительной степени способствовали удовлетворенности пассажиров и обеспечили более плавное и надежное перемещение внутри здания. Кроме того, повышенная эффективность наших систем соответствует целям управления энергопотреблением зданий, поскольку она сводит к минимуму ненужные движения и время простоя. Результаты демонстрируют способность системы соответствовать требованиям динамичной среды с высокой загруженностью и знаменуют собой значительный шаг вперед в интеллектуальном управлении инфраструктурой.

Ключевые слова: интеллектуальное управление агентом, оптимизация системы лифта, время ожидания пассажира.

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